SUITABILITY OF A GENETIC ALGORITHM FOR ROAD TRAFFIC NETWORK DIVISION

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Keywords: Traffic Network Division, Genetic Algorithm, Multi-objective Optimization.

Abstract: In this paper, the suitability of a genetic algorithm as a part of a method for division of road traffic network is discussed. The division of traffic network is necessary during the adaptation of the road traffic simulation for distributed computing environment. This environment enables to perform detailed simulation of large traffic networks (e.g. entire cities and larger) in a reasonable time. Genetic algorithms are considered, since they are often employed in both graph partitioning and multi-objective optimization problems. These problems are closely associated with the problem of road traffic network division.

1 INTRODUCTION

The computer simulation of road traffic is an important tool for analysis and control of road traffic networks. However, a detailed simulation of large areas (e.g. entire cities) can still require unsuitable amount of computational time. Therefore, many simulators have been adapted for distributed computing environment (Nagel and Rickert, 2001, Gonnet, 2001). In this environment, the combined power of multiple interconnected computers (nodes) is utilized to speed up the simulation. The traffic network is divided into sub-networks, which are then simulated by simulation processes running on particular nodes of the distributed computer.

The division of the network can affect the performance of the resulting distributed simulation. There are two main issues, which should be considered during the simulation – the similar load of the simulation processes and minimal inter-process communication among them. There are many methods for division of traffic network, which consider one of the issues, both, or neither.

In this paper, the suitability of a genetic algorithm (GA) as a part of a method for division of road traffic network is discussed. Genetic algorithms are considered, since they are often employed in both graph partitioning (Menouar, 2010) and multi-objective optimization (Farshbaf and Feizi-Darakhshi, 2009) problems, which are closely associated with the problem of road traffic network division.

2 TRAFFIC NETWORK DIVISION

As it was said, there are two issues, which should be considered during the traffic network division. Both issues are described in following subsections.

2.1 Load-balancing of Sub-networks

The similar load of the simulation processes is necessary, because all simulation processes are synchronized. Hence, the maximal speed of the simulation is determined by the slowest process (Cetin et al., 2003). So, the distributed simulation can achieve maximal speed, when the load of all simulation processes is similar and all processes require similar time to be performed.

The load of the simulation processes depends primarily on the number of vehicles moving within the simulated sub-networks. The reason is that the movement of the vehicles is the primary and most computation-consuming activity of the simulation.

If the load-balancing issue is considered during the traffic network division, the common approach is to use some feature of the traffic network as a representative weight for the load of the network. The network is then divided in a way that the sub-networks have similar weights, whose sum is equal to the weight of entire traffic network. The weight can be for example cumulative length of traffic lanes (Nagel and Rickert, 2001) or number of vehicles

Potuzak T..
SUITABILITY OF A GENETIC ALGORITHM FOR ROAD TRAFFIC NETWORK DIVISION.
DOI: 10.5220/0003657204400443
In *Proceedings of the International Conference on Knowledge Discovery and Information Retrieval* (KDIR-2011), pages 440-443
ISBN: 978-989-8425-79-9

moving within the lanes (Gonnet, 2001).

2.2 Low Inter-process Communication

The minimal inter-process communication is necessary, because it is relatively slow in comparison to other activities in the distributed simulation. The communication is required for the transfer of vehicles between the particular neighbouring traffic sub-networks and also for synchronization.

The number of messages for vehicles transfer is affected by the number of traffic lanes interconnecting the traffic sub-networks. Therefore, it is convenient to minimize this number during the traffic network division. Graph partitioning methods such as orthogonal recursive bisection can be employed for this purpose (Nagel and Rickert, 2001).

3 GENETIC ALGORITHMS (GA)

Now, as we discussed traffic network division issues, we can proceed with genetic algorithms.

3.1 General Concept

Genetic algorithms (GA) are evolutionary algorithms that mimic natural genetic evolution and selection in nature (Menouar, 2010). Developed by John Holland at the University of Michigan (Holland, 1975), they are widely used for solving of searching and optimization problems in many domains including multi-objective optimization (Farshbaf and Feizi-Darakhshi, 2009).

3.2 Basic Phases and Notions

Using a genetic algorithm, it is first necessary to define representation of a problem solution. Usually, a solution or an *individual* is represented by a vector of binary or integer values. When the representation is specified, an initial set of individuals is generated. This set is called *initial population* (Menouar, 2010).

For all individuals of the set, a *fitness function* is calculated. This function represents an assessment of the individual (Menouar, 2010) depending on problem domain. It can favour one criterion or be multi-objective (Farsh-baf and Feizi-Darakhshi, 2009).

A number of individuals with best fitness are selected. The *crossover* and *mutation* are then used to produce a new population (Farshbaf and Feizi-Darakhshi, 2009). By crossing, a new offspring is produced using two parents. The mutation is represented by random change(s) in the individual's representation (Bui and Moon, 1996).

The whole process repeats until certain number of iterations is reached (Menouar, 2010) or a stop condition is fulfilled (Bui and Moon, 1996).

4 GA FOR NETWORK DIVISION

Genetic algorithms should be suitable for traffic network division, since they are convenient for graph partitioning and multi-objective optimization. The equal load of the simulation processes and minimal number of connecting traffic lanes between them are the two objectives of the network division.

4.1 Problem Formulation

The genetic algorithm can optimize both criterions using the correct fitness function. Its input is the traffic network, which shall be divided into required number of sub-networks. Moreover, for the load-balancing of the sub-networks, it is necessary to add information about the vehicles, because the load of the sub-networks depends primarily on the number of vehicles moving within them (see Section 2.1).

4.2 Assigning Weights to Traffic Lanes

The information about the vehicles can be added as the weights of particular traffic lanes. These weights express the mean number of vehicles moving in the lanes during the simulation run.

However, the acquisition of this information from the sequential run of the simulation can be problematic due to memory and time requirements. Still, this approach can be found in (Gonnet, 2001).

Another solution is to use a less detailed simulation, which is fast enough to be performed sequentially in a suitable time. The fidelity of such less-detailed simulation is lower than the fidelity of the simulation, but sufficient to be used for the network division (Potuzak, 2011).

4.3 Dividing Network using GA

So, the genetic algorithm has the weighted traffic network as its input. Its output is the assignment of the crossroads to the particular sub-networks. This information is sufficient for marking of traffic lanes, which shall be divided to form the required number of sub-networks (the ultimate goal of the traffic network division). It is only necessary to mark traffic lanes connecting crossroads assigned to different sub-networks (Potuzak, 2011).

4.4 Representation of Individual

The first step in design of a genetic algorithm is to determine the representation of an individual. In this case, an individual can be represented by a vector of integers with the size corresponding to the total number of crossroads K. Then, each vector index represents a crossroad and its value represents the sub-network, to which the crossroad is assigned (see Fig. 1). So, the maximal value of an integer corresponds to the number of required sub-networks M.

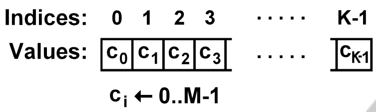

Figure 1: Representation of an individual.

In the initial population of 90 individuals, the crossroads are randomly assigned to the sub-networks. Using the fitness function, crossover, and mutation, this assignment changes towards a solution, where the sub-networks are load-balanced and the number of divided lanes is minimal.

4.5 Fitness Function

Considering the statements from previous sections, the fitness function consists of two parts – the *equability* representing the equal load of the sub-networks and the *compactness* representing the minimal number of divided traffic lanes. The equability of an individual can be calculated as:

$$E = 1 - \frac{\sum_{i=1}^{M} \frac{\left| w_{Si} - \overline{w_S} \right|}{\overline{w_S}}}{M}, \qquad (1)$$

where E is the equability of an individual, $\overline{w_S}$ is the mean total weight of one traffic sub-network, w_{Si} is the total weight of the i*th* sub-network, and M is the number of sub-networks.

The compactness C is very important for minimization of the number of divided traffic lanes. It can be calculated as the ratio of the number of undivided traffic lanes and the total number of traffic lanes.

Due to different requirements for the traffic network division results in different situations, it is possible to set the equability ratio in the fitness function. Hence, it can be calculated as:

$$F = r_E \cdot E + \left(1 - r_E\right) \cdot C, \qquad (2)$$

where, F is the fitness function of an individual, E is its the equability, C is its compactness and r_E is the ratio of the equability in the fitness function. The r_E can be set from 0.0 to 1.0. For a standard situation, the r_E has the value from 0.25 to 0.5.

4.6 Crossover and Mutation

After the initial population of 90 individuals is generated (see Section 4.4), the fitness value is calculated for each individual. Based on the fitness value, 10 individuals are selected to be “parents” of the next generation. The size of population and the number of selected individuals have been selected based on preliminary tests. The next generation is created using the crossover and mutation operators on the selected individuals (see Fig. 2).

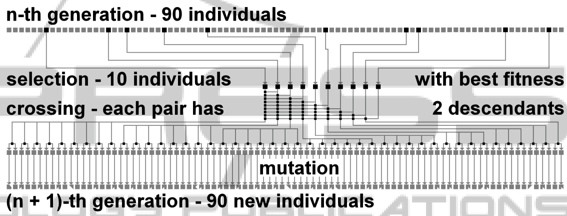

Figure 2: Creation of new generation of individuals.

Using all combinations of 10 selected individuals, a new generation of 90 individuals is created and the entire process repeats until preset number of generations is reached.

5 TESTS AND RESULTS

The suitability of the genetic algorithm for traffic network division was tested. Two sets of tests were performed as described in following sections.

5.1 Fitness Dependencies

The first set of tests was focused on the dependencies of the maximal achieved fitness on the size of the traffic network, the number of sub-networks, and the number of generations. Three regular square grids of 64, 256, and 1024 crossroads divided into 2, 4, and 8 sub-networks were used for testing. The number of generations ranged from 100 to 100000. The r_E ratio was set to 0.5.

The results (averaged from ten attempts) are depicted in Fig. 3. The maximal achieved fitness increases with increasing number of generations. This is an expectable behaviour, since more generations offer more time for convergence to the best solution. Another observation is that the maximal achieved fitness decreases with increasing number of crossroads and sub-networks. This is caused in both cases by higher complexity of the individuals due to increasing length or increasing number of possible values in the individuals, respectively.

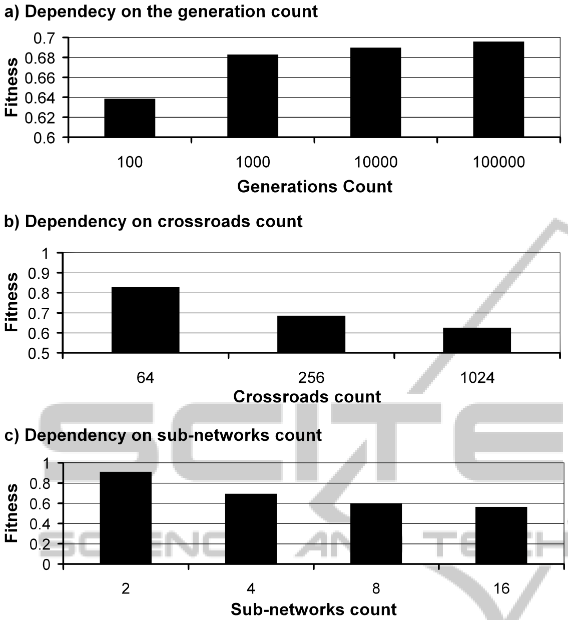

Figure 3: Dependencies of the maximal achieved fitness.

5.2 Time Performance of the GA

The second set of tests was focused on the time performance of the genetic algorithm, which depends on both the size of the traffic network and the number of generations. It was tested using a regular square grid of 64, 256, and 1024 crossroads, respectively. For each traffic network, the genetic algorithm was performed using 100, 1000, 10000, and 100000 generations. The network was always divided into two sub-networks. Both dependencies can be observed in Fig. 4.

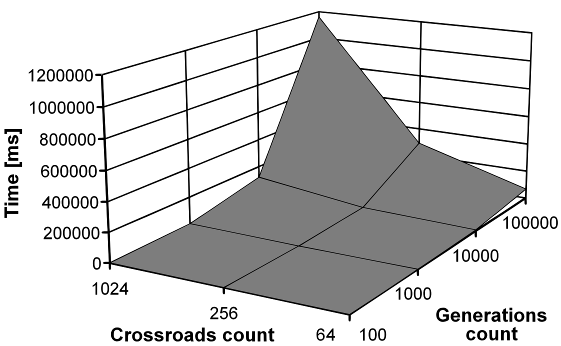

Figure 4: Dependency of the GA time performance.

Both time dependencies on the network size and generations count are linear (note logarithmic scale of the x- and y-axis and linear scale of the z-axis).

6 CONCLUSIONS

In this paper, we discussed the suitability of a genetic algorithm for division of the weighted traffic network. Considering the results of the performed sets of tests, it can be concluded that the genetic algorithm is suitable for the traffic network division. Its computation time is linearly dependent on the size of traffic network and the number of generation count. This makes it usable even for large networks.

In our future work, we will focus on further improvements of the designed genetic algorithm.

ACKNOWLEDGEMENTS

This work is supported by the Ministry of Education, Youth, and Sport of Czech Republic – University spec. research – 1311.

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